A Comparative Study of Selected Regression Models Using Road Traffic Crashes Data in Ekiti State

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Abstract **- Road traffic crashes are count (discrete) in nature, when modelling discrete data for characteristics and prediction of an event when dependent variable are non-negative and have integer values, it is appropriate to use Poisson regression. However the condition that the mean and variance of Poisson are equal poses a great constraints. Data on road traffic crashes from Federal Road Safety Commission (FRSC) Ekiti state Nigeria were analyzed using R software package. The result from the three existing model were compared using AIC, BIC and Deviance, with Generalized negative binomial showing an AIC value of 414.79 and BIC value of 490.8873 and negative binomial showing AIC value of 476.8 and BIC value of 495.59 and Poisson regression showing AIC value of 587.312 and BIC value of 589.321.Having shown a smaller value of AIC and BIC, Generalized negative binomial regression was consider a better model when analyzing road traffic crashes in Ekiti State Nigeria.**

Keywords**-Poisson regression model, Negative binomial regression, Generalized negative binomial regression.**

I. INTRODUCTION

The demand for transportation is rapidly increasing in the age of globalization, mobility is the key driver of economic growth, and hence expansion within transportation is a necessity. The increasing important of transportation does not only demand new standard for efficiency but also for safety precaution[11].When modelling count data for characteristics and prediction of an event where the dependent variable are non-negative and integer value, it is appropriate to use Poisson regression model but according to[6] Poisson regression is not appropriate when data exhibit over dispersion, and negative binomial addresses the issue of over-dispersion by including a dispersion parameter to accommodate the unobserved heterogeneity in the data [4]. Various factors such as data clustering and misspecifications of model lead to over dispersion in the data. Another importance of negative binomial is that, it is the mixture of family of Poisson distribution with gamma mixing weight[7] .Generalized negative binomial reduces to binomial or negative binomial distribution because the mean and the variance are approximately equal which is an advantage over the Poisson regression[8]

II. METHODS

A. Poisson Regression Model

The Poisson regression models are generalized linear models (GLM) with logarithm as the link function. In statistics the generalized linear model (GLM) is a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution. A generalized linear model is made up of a linear predictor

$$y_i = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_p x_{p_i} + \varepsilon_i \qquad (1)$$

And two functions, A Link function that describes the mean,

$E(y_i) = \mu_i$ Depends on the linear predictor $g(\mu_i) = y_i$

(2)

A variance function that describes the variance,

$V(y_i)$ Depends on the mean $V(y_i) = \phi V(\mu)$

(3)

Suppose $y_i \sim$ Poisson Then, $E(y_i) = \lambda_i$ and $V(y_i) = \lambda_i$

(4)

The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function. Link function here is the function that links the linear model in a design matrix and the Poisson distribution function.

Consider a linear regression model given as

$$y_i = \beta_0 + \beta_1 x_1 + \varepsilon_i = 1, \ldots, k \qquad (5)$$

If $y_i = \beta_0 + \beta_1 x_1 + \varepsilon_i = 1, \ldots, k$,

$x\varepsilon\square^{n}$ is a vector of independent variable then

$$Y = X\beta + \varepsilon \qquad (6)$$

Where $X$is an $n \times (k+1)$ vector of independent variables or predictor, and a column of 1's β *is a* $(k+1)$ by 1 vector of unknown parameters and ε is an $n \times 1$ *vectorof* random error terms *with* zero mean .Hence

$$E(Y / X) = x\beta \qquad (7)$$

Recall that, for Generalized Linear Models, we use the link function to transform Y:

That is,

$$G(Y) = \log_e(Y) \tag{8}$$

Therefore, this can be written more compactly as

$$\log_e E(Y/X) = x\beta \tag{9}$$

Thus, given a Poisson regression model with parameter β and an input vector x, the predicted mean of the associated Poisson distribution is given by

$$E(Y/X) = e^{x\beta} \tag{10}$$

If y_i, are independent observations with corresponding values x_i of the predicted variables, then β can be estimated by maximum likelihood. The maximum-likelihood estimates lack a closed-form expression and must be found by numerical methods. The probability surface for maximum-likelihood Poisson regression is always convex, making Newton-Raphson or other gradient-based methods appropriate estimation techniques.

Therefore, let y_i be the random variable, that takes non-negative values, i=1,2,…,n, Where n is thenumber of observations. Since y_i follows a Poisson distribution, the probability mass function is (pmf)

$$P(Y_i = y_i) = \frac{\lambda_i^{y_i} e(-\lambda_i)}{y_i!},\ y_i = 0,1,2,3... \tag{11}$$

$$P(Y = y) = f(y) = \frac{e^{-\lambda}\lambda^{y}}{y!}\ , y_i = 0,1,2,3... \tag{12}$$

With mean and variance as

$$E(y) = V(y) = \lambda \tag{13}$$

Where the conditional mean or predicted mean of the Poisson distribution is giving in (10) above specified by

$E(Y_i) = e^{x\beta} = \lambda_i$ (Same as the mean of the Poisson)

X is the value of the explanatory variable and $\beta = (\beta_1, \beta_2, ..., \beta_q)$ are the unknown k-dimensional vector of regression parameter.

The mean of the predicted Poisson distribution is given by $E(Y/X)$ and variance of y_i as $V(Y/X)$.

The parameter β can be estimated by maximum likelihood estimation method as follows;

$$\ell(\beta) = \prod_{i=1}^{n} \frac{\lambda_i^{y_i} e(-\lambda_i)}{y_i!} \tag{14}$$

The log-likelihood function is given by

$$ln\ell(\beta) = \sum_{i=1}^{n}\left[-\lambda_i + y_i \ln\lambda_i - \ln y_i!\right] \tag{15}$$

Substituting $\lambda_i = e^{x\beta}$ in the equation above, we have

$$ln\ell(\beta) = \sum_{i=1}^{n}\left[y_i(x\beta) - e^{x\beta} - \ln y_i!\right] \tag{16}$$

Differentiating equation (17) with respect to β and equating to zero, we have

$$\frac{\partial \ln\ell(\beta)}{\partial\beta} = \sum_{i=1}^{n}\left[y_i - e^{x\beta}\right]x = 0 \quad \text{i=1,2,…,k} \tag{17}$$

$$\frac{\partial^2 L}{\partial\beta\partial\beta'} = -\sum_{i=1}^{n}\left(e^{x_i'\beta}x_i' x_i\right) \tag{18}$$

$$\frac{\partial^2 L}{\partial\beta\partial\beta'} = -\sum_{i=1}^{n}\left(e^{x_i'\beta}x_{ij}x_{ii}\right);\ j,i = 1,2...p \tag{19}$$

$$E\left(\frac{\partial^2 L}{\partial\beta_j\partial\beta_i'}\right) = -\sum_{i=1}^{n}\left(e^{x_i'\beta}x_{ij}x_{ii}\right);\ j,i = 1,2...p \tag{20}$$

And the information matrix is;

$$k = \sum_{i=1}^{n}\left(e^{x_i'\beta}x_i' x_i\right) \tag{21}$$

$$\frac{\partial^2 L}{\partial\beta_j\partial\beta'_i} = -\sum_{i=1}^{n}\left(e^{x_i'\beta}x_{ij}x_{ii}\right) \tag{22}$$

$$k_{ji} = E\left(\frac{\partial^2 L}{\partial\beta_j\partial\beta_i'}\right) = -\sum{}_{i=1}^{n}\left(e^{x_i'\beta}x_{ij}x_{ii}\right) \tag{23}$$

$$k_{jir} = \left(\frac{\partial^3 L}{\partial\beta_j\partial\beta_i\partial\beta_r}\right) = -\sum{}_{i=1}^{n}\left(e^{x_i'\beta}x_{ij}x_{ii}\right) \tag{24}$$

$$k_{ij}^{(r)} = \frac{\partial k_{ji}}{\partial\beta_r} = -\sum_{i=1}^{n}\left(e^{x_i\beta}x_{ij}x_{ii}x_{ir}\right);\ j,l,r = 1,2,3...p \tag{25}$$

B. *Negative Binomial Regression (NBR)*

The negative binomial distribution can be viewed as a generalization of the Poisson distribution. The negative binomial can be viewed as a Poisson distribution where the Poisson parameter is itself a random variable, distributed according to a Gamma distribution. Thus the negative binomial distribution is known as Poisson-Gamma mixture.

As the most common alternative to Poisson regression, the negative binomial regression addresses the issue of over-dispersion by including a dispersion parameter to accommodate the unobserved heterogeneity in the count data. The negative binomial regression (Poisson-Gamma) can also be considered as generalization of Poisson regression. As its name implied, the negative binomial (Poisson-gamma) is a mixture of two distributions

The probability mass function for negative binomial regression is

$$f(y_i;\alpha,\mu_i)=\frac{\Gamma(\alpha+y_i)}{\Gamma(\alpha)\Gamma(y_i+1)}\left[\frac{\alpha}{\mu_i+\alpha}\right]^{\alpha}\left[\frac{\mu_i}{\mu_i+\alpha}\right]^{y_i} \quad (26)$$

The mean and variance are :

$$E(y_i;\alpha,\mu_i)=\mu_i \quad (27)$$

$$\mathrm{var}(y_i;\alpha,\mu_i)=\mu_i+\frac{\mu_{i^2}}{\alpha} \quad (28)$$

The next steps consist of defining the log-likelihood function and it can be shown that,[3], page 81)

$$In\left(\frac{\Gamma\left(y_i+\alpha^{-1}\right)}{\Gamma\left(\alpha^{-1}\right)}\right)=\sum_{j=0}^{y_i-1}\ln\left(j+\alpha^{-1}\right) \quad (29)$$

C. *Generalized Negative Binomial*

The generalized negative binomial distribution was developed by compounding the negative binomial distribution with another parameter which takes into account the variations in the mean and the variance. The parameter is such that both the mean and the variance are positively correlated with the value of the parameter, though the variance increases or decreases faster than the mean. The generalized negative binomial distribution reduces to the binomial or the negative binomial distribution as particular cases and converges to a Poisson-type distribution in which the variance may be more than, equal to or less than the mean, depending upon the value of the parameter[8]. The model is defined as follows;

$$=\binom{n+x\beta}{x}\frac{\Gamma n+x\beta+1}{x!\Gamma(n+x\beta-x+1)} \quad (32)$$

Taking $z=\alpha/(1-\alpha)$ the expression given a general identity as, $1=\sum_{x=0}^{\infty}b_\beta(x,n,\alpha)$ then

$$B_\beta(x,n,\alpha)=\frac{n\Gamma n+x\beta}{x!\Gamma(n+x\beta-x+1)}\alpha^x(1-\alpha)^{n+\beta x-x}, n>0, x=1,2,3,... \quad (33)$$

$b_\beta(x,n,\alpha)=0,\forall x\le n$ Such that $n+\beta_m<0$

Where $\sum(n)=\lambda(n+1)=a(b+n+1)$, the function $g_n(x)=f_{NB}(n;b+1,e^{-ax}),n=0,1,2...$ can be thought as the solution of chapman Kolmogorov differential equation with transition rate as $\sum(n)=n\ge 0$ that linking increasing from the previous comment results proved by

[5] then the solution of the system of the differential equation is given by

$$P_{l,n(x)}=\mathrm{g}_{n-1}(\mathrm{x})=f_{NB}(n-1;b+1),e^{-ax})$$

$$\binom{b+n-1}{n-1}\left(e^{-ax}\right)^{b+1}\left(1-e^{-ax}\right)^{n-1}\forall,n\le 1 \quad (34)$$

$$P\{\mathrm{Y(t)=n}\}=\int_0^1\binom{b+n-1}{n-1}\left[e^{-a(t-\tau)b+1}\right]\left[1-e^{-a(t-\tau)}\right]^{n-1}\lambda_0e^{-\lambda_0}dt \quad (35)$$

$$=\binom{b+n-1}{n-1}\lambda_0\int_0^t e^{-a(t-t)(b+1)}e^{-\lambda_0t}\left[1-e^{-a(t-\tau)}\right]^{n-1}dt \quad (36)$$

And substituting x = t in the last integral it follows that;

$$P\{\mathrm{Y(t)=n}\}=\binom{b+n-1}{n-1}\lambda_0e^{-\lambda_0t}\int_0^t e^{(\lambda_0-a(b+1))\mathrm{x}}\left(1-e^{-ax}\right)^{n-1}dx \quad (37)$$

$$=\binom{b+n-1}{n-1}\lambda_0e^{-\lambda_0t}\int_0^t(e^{-ax})^{b+1-\lambda_0/a}\left(1-e^{-ax}\right)^{n-1}dx \quad (38)$$

Finally consider $y=e^{-ax}$ in the integral of n≥1 that

$$P\{\mathrm{Y(t)=n}\}=\binom{b+n-1}{n-1}\frac{\lambda_0e^{-\lambda_0t}}{a}\int_{e^{-at}}^1 y^{b-\lambda_0/a[1-y]^{n-1}} \quad (39)$$

Hence the probability distribution function of the generalized negative binomial model is determined by

$$P\{\mathrm{Y(t)=0}\}=e^{-t\lambda_0}$$

And

$$P\{\mathrm{Y(t)=n}\}=\binom{b+n-1}{n-1}\frac{\lambda_0e^{-\lambda_0t}}{a}\int_{e^{-at}}^1 y^{b-\lambda_0/a[1-y]^{n-1}} \quad (40)$$

Mean $=n\alpha\left[1+\beta\alpha+\left(\beta\alpha\right)^2+...\right]=\dfrac{n\alpha}{\left(1-\beta\alpha\right)}$ (41)

$$\mu_2 = \frac{n\alpha(1-\alpha)}{(1-\beta\alpha)^3} \tag{42}$$

Consider $Y_1, Y_2, \ldots, Y_n$ a random sample of Y(1) whose distribution is given by;

$$L(\lambda_0, a, b) = \prod_{i-1}^{n} P(Y_i = y_i) \tag{43}$$

$$\prod_{i:y_i=0} P(Y_i = y_i) \prod_{i:y_i>0} P(Y_i = y_i) \tag{44}$$

$$\prod_{i:y_i>0} e^{-\lambda_0} \prod_{i-1}^{n} \binom{b+y_i-1}{y_i-1} \frac{\lambda_0 e^{-\lambda_0 t}}{a} \int_{e^{-at}}^{1} x^{b-\lambda_0/a[1-x]^{y_i-1}} dx \tag{45}$$

$$\frac{e^{-n_0\lambda_0}\lambda_0^{(n-n_0)} e^{-(n-n_0)\lambda_0}}{a^{n-n_0}} \times \prod_{i:y_i>0}^{n} \binom{b+y_i-1}{y_i-1} \frac{\lambda_0 e^{-\lambda_0 t}}{a} \int_{e^{-at}}^{1} x^{b-\lambda_0/a[1-x]^{y_i-1}} dx \tag{46}$$

$$\frac{e^{-n_0\lambda_0}\lambda_0^{(n-n_0)}}{a^{n-n_0}} \times \prod_{i:y_i>0}^{n} \binom{b+y_i-1}{y_i-1} \frac{\lambda_0 e^{-\lambda_0 t}}{a} \int_{e^{-at}}^{1} x^{b-\lambda_0/a[1-x]^{y_i-1}} dx \tag{47}$$

Where $Y_1, Y_2, \ldots, Y_n$ are observed value of $Y(i), n_0 = \sum_{j=1}^{n} \mathrm{l}(0)\, \mathrm{y}_i$ is the number of zero in the sample

$\lambda_0 > 0, a > 0$ And $b = -1$ thus the likelihood function is obtained by

$$l(\lambda_0, a, b) = n\lambda_0 + (n-n_0)(\log(\lambda_0 - \log(a)) + \sum \log \binom{b+y_i-1}{y_i-1} \int_{e^{-at}}^{1} x^{b-\lambda_0/a[1-x]^{y_i-1}} dx \tag{48}$$

To improve the performance of the maximization and logarithm used to obtain the maximum likelihood estimation the following parameterization will be considered $l_0 = \log\lambda_0, l_a = \log(a), l_b = \log(b+1)$ hence the likelihood function for the parameterization is expressed as follows

$$l(l_{o,} l_a, l_b) = -ne^{l_0} + (n-n_0)(l_0 - l_a) \sum_{i:y_i>0} \log \binom{e^{l_b} + y_i - 2}{y_i - 1} \int_{\exp(-e^{l_a})}^{1} x^{e^{l_b} - e^{l_0 - l_a - 1}} (1-x)^{y_i - 1} dx \tag{49}$$

By substituting equation (29) into (26), the log-likelihood can be computed using the equation

$$L = \sum_{i=1}^{n} \{\ln[\Gamma(y_i + \alpha^{-1})] - \ln[\Gamma(y_i + 1) - \alpha^{-1}\ln(1+\alpha\mu_i) - y_i \ln(1+\alpha\mu_i) + y_i \ln(\alpha) + y_i \ln(\mu_i)] \tag{50}$$

Therefore, the log-likelihood function become [3], page 81)

$$L = \sum_{i=1}^{n} \left\{ \begin{array}{l} \left(\sum_{j=0}^{y_i-1} \ln(j+\alpha^{-1}) \right) - \ln(\Gamma(y_i+1) - (y_i + \alpha^{-1}) \\ \ln(1+\alpha\mu_i) + y_i \ln(\mu_i) + y_i \ln(\alpha) \end{array} \right\} \tag{51}$$

D. A Multicollinearity Test

In statistics muticollinearity is a phenomenon in which one predictor variable in multiple regression model can be linearly predicted from the other with a substantial degree of accuracy. Multicollinearity occur when there are high correlation between two or more predictor variable, which skewing the result in regression model. One of the formal ways of detecting muticollinearity is by the use of the variance inflation factor (VIF).VIF is the quotient of the variance in a model with multiple term.it qualifies the severity of muticollinearity in the least square regression analysis. A VIF value of 10 and above indicates a multicollinearity problem.

$$VIF = \frac{I}{R_j^2}$$

Where R_j^2 is the coefficient of determination of a regression of explanatory variable j on all the other explanatory.

Tolerance is a useful tool for diagnosing muticollinearity which happen when variable are too closely related, and tolerance is associated with each independence variable and range from 0 to 1.Allison (1990) noted that there is not a strict cutoff for tolerance, but suggests a tolerance below 0.40 is cause for concern.[10] stated that any value under 0.20 suggest serious muticollinearity in the model.

High tolerance (e.g. 0.84) =low multicollinearity

Low tolerance (e.g. 0.19) =high muticollinearity

E. Akaike Information criterion (AIC)

The Alkaike information criterion (AIC) is a measure of the relative quality of a statistical model for a given set of data. That is given a collection of model for the data, AIC estimates the quality of each model, relative to each of the model. Hence AIC provides a mean for model selection, given a set of candidate models for the data, the preferred model is the one with the minimum AIC value(i.e the smaller the AIC value, the better the model).it was also mention that Akaike Information criterion is one of the most commonly used fit statistics. It has a formula

AIC (l) = -2(L-K)

AIC (n) =2/n (L-K)

Note that K is the number of predictors including the intercept, AIC is usually outputted by statistical software application

F. Bayesian Information criterion (BIC)

It was also mentions that Bayesian information criterion as another common fit statistic. It has three formula

BIC(R) =D-(df) In (n)

BIC (L) =2L+Kin (n)

BIC (Q) =2/n(L-Kin(k)

III. RESULT AND DISCUSSION

A secondary data was collected from Federal Road Safety Commission (FRSC),Ekiti Sector Command Ado-Ekiti, Nigeria. Monthly data of the number of traffic fatality was collected from January 2010 – December 2018 and the data was analysis by R software package

The data was analysis using R software package.

Before performing the analysis on the three models used, testing the data for multicollinearity was conducted. The test result are shown in table A below:

TABLE 1: COLLINEARITY STATISTICS

Model	**Tolerance**	**VIF**
Season(Month of the Year)	1.0125	0.9876
Number of causes	4.8826	0.2048
Vehicles Involve	4.0477	0.2471
Number Injured	1.8804	0.5318
Number killed	1.233	0.8108

Table 1 shows that all the variables have VIF values < 10, using rule of thumb since they are all less than 10, there is no multicollinearity. Thus all the variable can be Included in the subsequent analyses and modelling with the Poisson regression, Negative Binomial regression and Generalized Negative Binomial.

TABLE 2: POISSON REGRESSION

Parameters	Estimate	Standard Error	Z value	Pr(>|z|)
Intercept	1.016912	0.165990	6.126	8.99e-10
Season(Month of the Year)	-0.008622	0.010712	-0.805	0.42085
Number of causes	0.017069	0.011436	1.493	0.00312
Vehicles Involve	0.045618	0.005069	8.999	< 2e-16
Number Injured	0.011159	0.003550	3.143	0.00167
Number killed	-0.003965	0.014258	-0.278	0.78096

Table 2 above shows the result of the Poisson regression using the p value in the last column season, number of causes, number of vehicle involved , number injured and have significant effect on road traffic crashes while others has no significant effect.

TABLE 3: NEGATIVE BINOMIAL REGRESSION

Parameters	Estimate	Standard Error	Z value	Pr(>|z|)
Intercept	1.016903	0.165995	6.126	9.01e-10
Season(Month of the Year)	-0.008622	0.010712	-0.805	0.42087
Number of causes	0.017069	0.011437	1.492	< 2e-16
Vehicles Involve	0.045618	0.005069	8.999	< 2e-16
No Injured	0.011160	0.003551	3.143	0.00167
No killed	-0.003964	0.014258	-0.278	0.78100

Table 3 shows the result of the negative binomial regression using the p value in the last column ; number of causes, number of vehicle involved , number injured have significant effect on road traffic crashes while others have no significant effect.

TABLE 4: GENERALIZED NEGATIVE BINOMIAL

Parameters	Estimate	Standard Error	Z value	Pr(>|z|)
Intercept	0.4937806	0.0132060	37.391	< 2e-16
Season(Month of the Year)	0.0044566	0.0013295	3.352	0.00113
Number of causes	0.0188368	0.0011600	16.238	< 2e-16
Vehicles Involve	0.0332233	0.0005804	57.237	< 2e-16
No Injured	0.0029701	0.0004539	6.543	2.45e-09
No killed	-0.0185590	0.0011766	-15.773	< 2e-16

Table 4 shows the result of the generalized negative binomial regression using the p value in the last column season of the year, number of causes, number of vehicle involved , number injured and no killed have significant effect on road traffic crashes.

TABLE 5: AIC, BIC AND DEVIANCE VALUES FOR THE THREE MODELS

Model	AIC	BIC	Deviance
Generalized negative binomial regression	**414.79**	**460.8873**	**61.93**
Negative binomial	476.8	495.57	66.927
Poisson regression	587.3196	589.3208	69.927

Comparison using AIC and BIC values in table 2,3 and 4 , the estimated AIC and BIC for the Poisson regression is 587.3196 and 589.3208 respectively, whereas it is 476.8 and 495.57 for Negative binomial and for Generalize Negative binomial is 414.79 and 460.8873 respectively. The smallest value of AIC and BIC is the generalized negative binomial regression and therefore it is the optimal model.

IV. DISCUSSION

Road traffic crashes are count(discrete) in nature, when modelling discrete data for characteristics and prediction of an event when dependent variable are non-negative and integer value it is appropriate using Poisson regression, however the condition that mean and variance of Poisson regression are equal to each other poses a great constraints. Hence necessitating the use of the Generalized negative binomial(GNB) and negative binomial(NBR) models, which does not require these constraints that the mean is equal to the variance as proxies Data on road traffic crashes from Ekiti state command of federal road safety commission Nigeria were analysed and the result from the three model were compared using Akaike information criterion(AIC) and Bayesian information criterion(BIC) and the deviance with Generalized negative binomial showing an AIC value of 414.79 , BIC value of 490.8873 and deviance value of 61.93.The generalized negative binomial regression using the p value suggested that season of the year, number of causes, number of vehicle involved , number injured and number killed have significant effect on road traffic crashes. Negative binomial regression gives an AIC value of 476.8, BIC value of 495.57 and deviance value of 66.93. Negative binomial regression indicates that value number of causes, number of vehicle involved , number injured have significant effect on road traffic crashes while others have no significant effect.Poison regression showing AIC value of 587.3196, BIC value of 589.3208 and deviance value of 69.93. Poisson regression using the p value season of the year, number of causes, ,number of vehicle involved , number injured have significant effect on road traffic crashes while others has no significant effect. Since the generalized negative binomial regression produced the smallest AIC and BIC value, then it can be consider as the best model when analysing road traffic crashes in Ekiti State, Nigeria.

V. CONCLUSION

Having compared the three models on road traffic crashes in Ekiti state Nigeria and the result from the three model were compared using AIC and BIC and with Generalized negative binomial having the smaller AIC and BIC ,Generalized negative binomial was considered as the best model for analysing road traffic crashes in Ekiti State, Nigeria.

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